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A note on the evolution of directional distance function and its development in energy and environmental studies 1997–2013

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ABSTRACT

Recently, a relatively new methodology named directional distance function (DDF) has been attracting positive attention in the field of energy and environmental (E&E) modeling. However, there is still no literature review on the application of DDF in E&E studies. This paper is intended to fill this gap. First, the most widely used DDF techniques and its extensions are briefly introduced. Second, this article attempts a classification of typical publications in this field. The main issues raised by the previous studies are discussed. Some guidelines for model selection and future directions are proposed for DDF related research in E&E studies.

Contents

1. Introduction

Environmental deterioration is one of the major side effects of economic growth. To begin addressing this issue, the concept of sustainable development was first presented in 1987 by the World

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Commission on Environment and Development. The Commission suggested the first official definition of sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [1]. Since then, there has been increasing interest in energy and environmental (E&E) modeling because E&E issues are key factors in sustainable development. For instance, different types of energy planning and management modeling are reviewed by [90]. Ang and Zhang [91] reviewed 124 studies related to index decomposition analysis (IDA) techniques to energy demand and gas emissions analysis. The applications of decision analysis in E&E studies have been reviewed by [92,93].

Among the wide spectrum of E&E modeling techniques, the distance function has drawn much attention, one possible reason being that it can model good and bad outputs (pollutants) simultaneously [2]. In addition, unlike the cost function, it does not require copious amounts of price-specific data and information. Given only the quantity data of inputs and outputs, using the distance function, one can model various critical characteristics, such as environmental technical efficiency, environmentally sensitive productivity growth, and the shadow prices of pollutants.

Generally, two kinds of distance functions are widely used in E&E studies: the Shephard distance function [3] and the DDF [4]. The Shephard distance function expands the good and bad outputs proportionally, to the extent feasible. Thus, this method does not credit reduction of bad outputs, since all outputs are expanded at the same rate. On the other hand, the DDF, a relatively new approach for E&E modeling, has attracted much attention. A major advantage of the DDF is that it is capable of expanding desirable outputs and contracting energy inputs or bad outputs simultaneously. Therefore, the DDF is a generalized form of the Shephard distance function and is more powerful and flexible than it.

One can estimate the DDF in at least two different ways: the non-parametric data envelopment analysis (DEA) approach and the parametric approach. The DEA estimation relies on mathematical programming, and it is based on the construction of a piecewise linear combination of all observed outputs and inputs. A major advantage of the DEA approach is that it does not need the imposition of a functional form on the underlying technology. Therefore, DEA can easily provide an estimate of efficiency and productivity. A review of DEA in E&E studies can be found in [5,6]. The parametric approach, which is not as widely used as DEA, requires the use of a functional form for the distance function. It has the advantage of providing an estimated parametric representation of the technology that is everywhere differentiable and easy to manipulate algebraically. Therefore, the parametric method is usually used to estimate shadow prices of pollutants. The applications of parametric distance function for shadow pricing can be found in [27,33,67,71] including Shephard distance function and DDF. This study mainly focuses on the review of non-parametric DDF that gains more popularity than the parametric one.

Although a large number of studies have employed the DDF approach in E&E analysis, to date, no study offers a comprehensive review of its applications in E&E modeling. Since a review of this topic would be very useful and timely, it is the purpose of this study to fill this gap by presenting a literature review on applications of the DDF in E&E studies.

The remainder of this paper is as follows. First, the basic DDF methodology is introduced, including environmental technology and the basic DDF model. Section 3 presents some extensions to basic DDF models derived from the literature review and the characteristics of the DDF itself. Section 4 classifies typical research using the DDF in E&E studies published in major journals from 1997 to 2013, by various relevant attributes. As part of the literature review, the main findings of previous studies are discussed. Finally, suggestions for model selection and directions for potential future studies are proposed.

2. Non-parametric DDF methodology

2.1. Environmental production technology

In order to introduce the basic DDF, which is a production frontier methodology in E&E studies, we first need to explain the term "environmental production technology". Assume that there are $j=1, \ldots, N$ decision-making units (DMUs). These can be electricity-generating units or manufacturing firms. Assume that each DMU uses inputs vector $x \in \Re_{+}^{M}$ to jointly produce outputs vector $y \in \Re_{+}^{S}$ and bad outputs $b \in \Re_{+}^{J}$. The multi-output production technology can be expressed as follows:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\} \tag{1}$$

where T is often assumed to satisfy the standard axioms of the production theory [7]. For instance, inactivity is always possible, and finite amounts of inputs can produce only finite amounts of outputs. In addition, inputs and desirable outputs are often assumed to be strongly or freely disposable. For a reasonable model of joint-production technologies, as described in [8], the weak disposability and null-jointness assumptions need to be imposed on T. Technically, the two assumptions can be expressed as follows:

(1) If $(x, y, b) \in T$ and $0 \le \theta \le 1$, then $(x, \theta y, \theta b) \in T$ and
(2) If $(x, y, b) \in T$ and $b=0$, then $y=0$.

The weak-disposability assumption implies that reducing bad outputs, such as carbon dioxide (CO_2) emission, in the production process are costly in terms of proportional reductions in products. The null-jointness assumption states that bad outputs (e.g., CO_2 emissions) are not avoidable in the production process and that the only way to remove all bad outputs is to stop production.

After specifying the environmental production technology T, the parametric distance function or the non-parametric DEA can be used to construct an environmental production technology. A major advantage of the DEA approach is that it does not need the imposition of a functional form on the underlying technology; therefore, we introduce the non-parametric DEA piecewise linear production frontier more easily to construct the environmental production technology. Then, T for N DMUs exhibiting constant returns to scale can be expressed as follows:

$$\begin{aligned} T = \Big\{ (x, y, b) : & \sum_{n=1}^{N} z_n x_{mn} \le x_m, m = 1, \ldots, M, \\ & \sum_{n=1}^{N} z_n y_{sn} \ge y_s, s = 1, \ldots, S, \\ & \sum_{n=1}^{N} z_n b_{jn} = b_j, j = 1, \ldots, J, \\ & z_n \ge 0, n = 1, \ldots, N \Big\} \end{aligned} \tag{2}$$

2.2. Directional distance function

Chung et al. [17] were the first to use the DDF introduced by [4] to examine environmental efficiency. The DDF is a relatively new methodology for environmental technology. Here, the basic DDF is defined such that it seeks to maximize desirable outputs, while reducing inputs and undesirable outputs simultaneously. Thus,

$$\vec{D}(x, y, b; \vec{g}) = \max\{\beta : (x - \beta \vec{g}_x, y + \beta \vec{g}_y, b - \beta \vec{g}_b) \in T\} \tag{3}$$

where $\vec{g} = (\vec{g}_x, \vec{g}_y, \vec{g}_b)$ is the vector of the directions in which the inputs and outputs should be scaled. β denotes a vector of scaling factors representing the inefficiency measure. The DDF allows for a range of direction vectors, depending on the purpose of the study (e.g., for policy targets). Combining Eqs. (2) and (3), one can estimate the DDF to measure environmental inefficiency of each DMU.

2.3. The Malmquist–Luenberger productivity index

The DDF described in (3) can be used for measuring relative environmental efficiency in a specific period. This is a static efficiency measure. Chung et al. [17] also proposed a Malmquist–Luenberger productivity index (MLPI) based on the DDF to measure environmentally sensitive productivity growth using time-series data. In order to define the MLPI, contemporaneous environmental technology is expressed as $T^t = \{(x^t, y^t, b^t) : x^t \text{ can produce } (y^t, b^t)\}$, where $t=1, 2, \ldots, T$. The contemporaneous environmental technology is constructed from DMUs of specific time t.

Let t and s $(t<s)$ denote two time periods. Assume that $D^t(x_n^t, y_n^t, b_n^t)$ and $D^s(x_n^t, y_n^t, b_n^t)$ are the DDFs of firm n based on its inputs and outputs for the environmental production technology at t and s, respectively. Furthermore, assume that $D^t(x_n^s, y_n^s, b_n^s)$ and $D^s(x_n^s, y_n^s, b_n^s)$, respectively, are the DDF of firm n based on its inputs and outputs for the environmental technology at period t and s. The MLPI is defined as

$$\text{MLPI}_n(t,s) = \left[\frac{1+D^t(x_n^s, y_n^s, b_n^s) \cdot 1+D^s(x_n^s, y_n^s, b_n^s)}{1+D^t(x_n^t, y_n^t, b_n^t) \cdot 1+D^s(x_n^t, y_n^t, b_n^t)} \right]^{1/2} \tag{4}$$

$\text{MLPI}_n(t,s)$ can be used to measure the environmentally sensitive productivity growth of DMU n from period t to period s. $\text{MLPI}_n(t,s) > 1$ (or $\text{MLPI}_n(t,s) < 1$) means that the productivity has improved (or deteriorated). Similar to the Malmquist productivity index (MPI), MLPI can also be decomposed into two components: efficiency change and technological change.

As shown in (4), MLPI measures productivity growth in a ratio way and based on the geometric mean of the DDFs. An alternative way to measure productivity growth is to use the Luenberger productivity index (LPI), which measures productivity growth in an additive way using the arithmetic mean of the DDFs in two periods. Based on Chambers et al. [9], the LPI is defined as

$$\text{LPI}_n(t,s) = \frac{1}{2} \left[\begin{array}{l} D^s(x_n^t, y_n^t, b_n^t) - D^s(x_n^s, y_n^s, b_n^s) \\ + D^t(x_n^t, y_n^t, b_n^t) - D^t(x_n^s, y_n^s, b_n^s) \end{array} \right] \tag{5}$$

3. Extensions to the basic DDF and the MLPI

3.1. Non-radial DDF

The conventional DDF described in (3) reduces undesirable outputs (inputs) and increases desirable outputs at the same rate β; it can be regarded as a radial efficiency measure, albeit with several limitations. One limitation is that a radial measure may overestimate efficiency when some slacks exist [10]. Fig. 1 visually explains why the radial DDF overestimates efficiency. The OABCDE area is assumed to be an output set corresponding to the environmental production technology defined in Eq. (2). For the point K located near the left side of the frontier, if the direction g is taken and the traditional radial DDF is used, then the point F is the benchmark point for evaluating K. However, if the non-radial DDF is used, then the benchmarking point is B because it produces a smaller quantity of undesirable outputs while generating the same quantity of desirable ones as F. Therefore, the distance BF is the

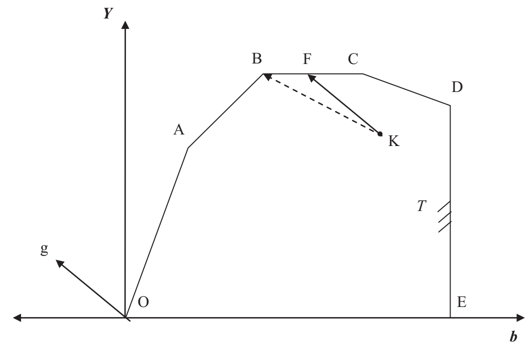


Fig. 1. Radial vs. non-radial DDF.

slack in the radial DDF and is referred to as "slack-bias" [10]. Because the radial DDF does not take this sort of slacks into account, it has the potential to reduce inefficiencies and thus may overestimate the efficiency score.

In addition, as Chang and Hu [46] argued, a radial efficiency measure cannot provide a single-factor efficiency measure, such as energy efficiency, because the DDF can only give the same rate of inefficiency. Several studies have extended the conventional DDF to the non-radial DDF (NDDF) by incorporating slacks into efficiency measurement [10–12]. Some studies have also employed the non-radial efficiency measure in E&E studies [13,46,77,83]

For E&E studies, Zhou et al. [77] were the first to provide a formal definition of the NDDF with bad environmental outputs as follows:

$$N\vec{D}(x, y, b; g) = \sup\{\mathbf{w}^T \boldsymbol{\beta} : ((x, y, b) + g \cdot diag(\boldsymbol{\beta})) \in T\} \tag{6}$$

where $\mathbf{w} = (w_m^x, w_s^y, w_j^b)^T$ denotes a normalized weight vector relevant to numbers of inputs and outputs, $g = (-g_x, g_y, -g_b)$ is an explicit directional vector, and $\beta = (\beta_m^x, \beta_s^y, \beta_j^b)^T \geq 0$ denotes the vector of scaling factors. Combining (2) and (5), we can compute the value of $N\vec{D}(x, y, b; g)$ by solving the following DEA-type model:

$$\begin{aligned} N\vec{D}(x, y, b; g) = \ & \max \ w_m^x \beta_m^x + w_s^y \beta_s^y + w_j^b \beta_j^b \\ & \text{s.t.} \sum_{n=1}^{N} z_n x_{mn} \leq x_m - \beta_m^x g_{xm}, \quad m = 1, \ldots, M, \\ & \sum_{n=1}^{N} z_n y_{sn} \geq y_s + \beta_s^y g_{ys}, \quad s = 1, \ldots S, \\ & \sum_{n=1}^{N} z_n b_{jn} = b_j - \beta_j^b g_{bj}, \quad j = 1, \ldots J, \\ & z_n \geq 0, \quad n = 1, 2, \ldots, N \\ & \beta_m^x, \beta_s^y, \beta_j^b \geq 0 \end{aligned} \tag{7}$$

If $N\vec{D}(x, y, b; g) = 0$, then the DMU to be evaluated is located on the best practice frontier in the direction of g, considering the slacks.

3.2. Extensions of the MLPI

To overcome some specific limitations of the MLPI, certain studies have devised extensions to the conventional MLPI based on the modifications to the environmental production technology.

3.2.1. Global MLPI

The conventional MLPI is defined in a geometric mean form, which has the disadvantage of not being circular. Moreover, it faces the potential linear programming infeasibility problem in measuring cross-period DDFs. Window analysis is usually used to overcome the infeasible solution problem [18,58]. An alternative approach is to use the Global MLPI (GMLPI). The GMLPI is constructed based on the global Malmquist index in [14]. In order to define the GMLPI, we need the global environmental production

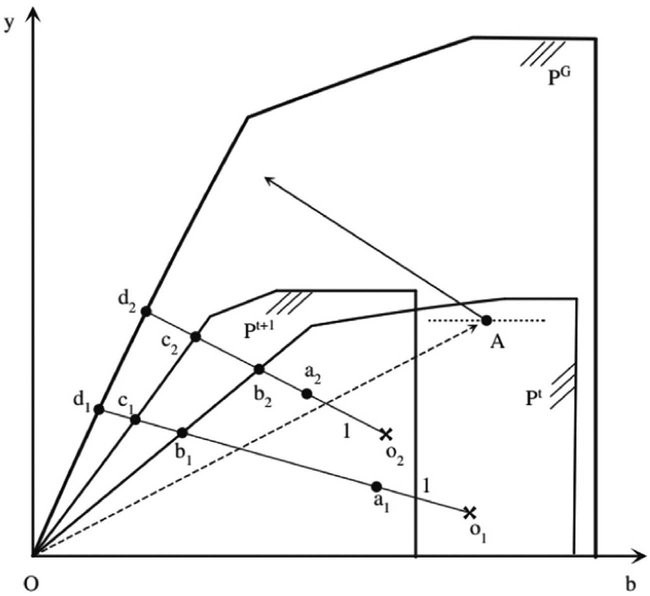


Fig. 2. Illustration of GMLPI approach.

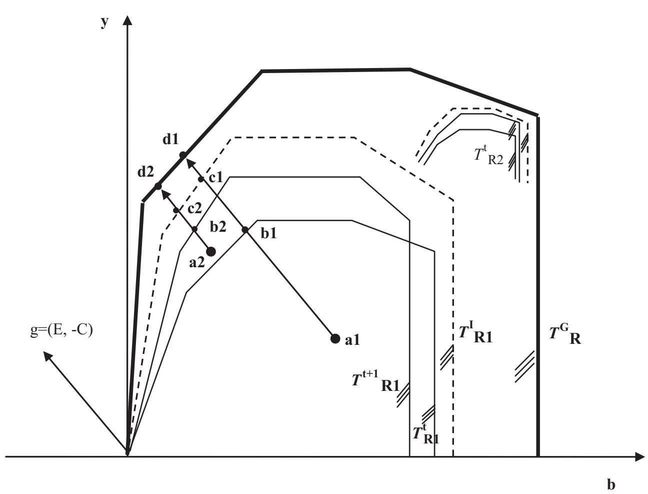


Fig. 3. Illustration of MMLPI approach.

technology, which is defined as $T^G = T^1 \cup T^2 \cup \cdots T^T$. That is, the global environmental production technology envelops all the contemporaneous environmental technologies into a single environmental technology. The GMLPI is then defined as the ratio of the two DDFs based on the global environmental production at period t and s, respectively. Fig. 2 illustrates the concept of GMLPI, the two interior solid lines are the contemporaneous environmental technologies for time period t and s, respectively, and the interior thick solid line is the global environmental technology. The DMU A in is a good example for the infeasibility problem of MLPI, because the $D^t(x_i^{t+1}, y_i^{t+1}, b_i^{t+1})$ is not feasible. The calculation process for the GMLPI can be found in [55].

3.2.2. Metafrontier MLPI

Although the conventional MLPI is a powerful tool for measuring environmentally sensitive productivity growth, it has a shortcoming in that it does not incorporate group heterogeneities in the productivity analysis. If group heterogeneities are not considered, the estimated MLPI might be biased because heterogeneity across groups might lead to a different production technology. The production environments of the DMUs of one group might be

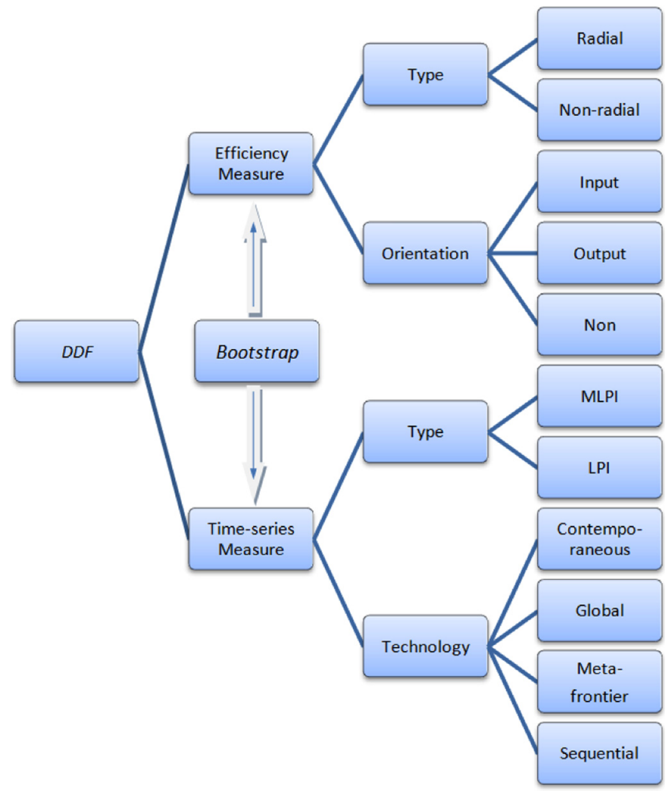


Fig. 4. The methodological structure of DDF model.

different from those of the other group. Therefore, one cannot directly compare the performance of DMUs operating under different production technologies [15,56]. The metafrontier MLPI (MMLPI) could be a suitable method to consider group heterogeneities in a conventional MLPI [56]. It constructs a group-frontier and a metafrontier separately to measure productivity growth. Fig. 3 shows the MMLPI and its decomposed components. This is a case of two groups (R_1, R_2) and two time periods (t, $t+1$). Here a_1 and a_2 are observed DMUs for the two periods t and $t+1$, respectively, and $T^t_{R_1}$ and $T^{t+1}_{R_1}$ represent the contemporaneous environmental production technology of group R_1 in periods t and $t+1$, respectively. $T^I_{R_1}$ is the intertemporal environmental production technology for group R_1, and $T_R{}^G$ is the global environmental production technology for two groups. One can refer to [56] for its calculation details.

3.2.3. Sequential MLPI

The DDF is usually estimated separately for each time period, and therefore, the resulting MLPI is constructed based on contemporaneous environmental technology. This conventional MLPI often translates into wide oscillations, because one cannot distinguish the shifts in frontier induced by random shocks or innovations in technology. To avoid this problem, sequential environmental production technology could be used to construct the MLPI, thus giving rise to the Sequential MLPI (SMLPI) [57]. The SMLPI is constructed by the DDF, which is calculated each time, including not only the current year, but also all the years preceding it. Therefore, SMLPI assumes that technological knowledge accumulates over time, which satisfies the nature of technology, that is, that technology always progresses or at least remains unchanged from the macroeconomic perspective. Details of the SMLPI can be found in [57].

Table 1
Previous E&E studies incorporating the DDF and their specific features.

Author	Reference number	Year	Country/region	Field of research and data	Major issues addressed	Methodological approaches			
						Efficiency measure		Time-series measure	
						Type	Orientation	MPI/LPI	Technology
Chung et al.	[17]	1997	Sweden	Paper and pulp mills	Environmentally sensitive productivity growth	R	O	MLPI	C
Färe et al.	[18]	2001	US	Manufacturing sectors	Conventional productivity growth and environmentally sensitive productivity growth	R	O	MLPI	C
Weber and Domazlicky	[19]	2001	US	Regional manufacturing industry	Environmentally sensitive productivity growth	R	O	MLPI	C
Arocena and Waddams Price	[20]	2002	Spain	Coal-fired power plants	Environmental efficiency and environmentally sensitive productivity growth	R	N	MLPI	S
Boyd et al.	[21]	2002	US	Container glass industry	Environmental efficiency, environmentally sensitive productivity growth, and shadow price of NO_x	R	O	MLPI	C
Lee et al.	[22]	2002	Korea	Fossil-fueled power plants	Environmental inefficiency and shadow price of pollutants	R	O	No	–
Ball et al.	[23]	2004	US	Regional agricultural farm	Environmental efficiency, environmentally sensitive productivity growth, and shadow price	R	N	MLPI	C
Domazlicky and Weber	[24]	2004	US	Chemical industry	Environmental regulatory impact and environmentally sensitive productivity growth	R	O	MLPI	C
Jeon and Sickles	[25]	2004	OECD and Asian economies	Country-level data	Traditional and bootstrapped environmentally sensitive productivity growth	R	O	MLPI	C
Shinji and Managi	[26]	2004	China	Province-level data	Environmentally sensitive productivity growth	R	O	MLPI	C
Färe et al.	[27]	2005	US	Electric utilities	Technical efficiency, shadow price and elasticity of substitution	R	O	No	–
Managi et al.	[28]	2005	US	Well-level data of the oil and gas industry	Relationship between environmental regulations and environmentally sensitive productivity growth	R	O	MLPI	C
Picazo-Tadeo et al.	[29]	2005	Spain	Ceramic tile producers	Environmental efficiency and environmental regulatory cost	R	N	No	–
Yörük and Zaim	[30]	2005	28 OECD countries	Country-level data	Environmentally sensitive productivity growth	R	N	MLPI	C
Färe et al.	[31]	2006	US	Agriculture industry	Technical efficiency and shadow prices	R	O	No	–
Kumar	[32]	2006	Various countries	Country-level data	Environmentally sensitive productivity growth	R	O	MLPI	C
Vardanyan and Noh	[33]	2006	US	Electric utilities	Shadow price	R	O	No	–
Färe et al.	[34]	2007	US	Coal-fired power plants	Environmental adjusted efficiency and environmental regulatory cost	R	O	No	–
McMullen and Noh	[35]	2007	US	Bus transit agencies	Efficiency with CO_2 and environmental regulatory cost	R	O	No	–
Piot–Lepetit and Moing	[36]	2007	France	Pig production farms	Environmentally sensitive productivity growth and environmental regulatory cost	R	O	MLPI	C
Watanabe and Tanaka	[37]	2007	China	Province-level industry data	Efficiency with SO_2 and determinants	R	O	No	–
Yörük	[38]	2007	28 OECD countries	Country-level data	Environmentally sensitive productivity growth	R	N	MLPI	C
Managi and Jena	[39]	2008	India	State-level manufacturing industry data	Environmental productivity and Kuznets curve	R	O	LPI	C
Nankano and Managi	[40]	2008	Japan	Steam power companies	Productivity growth and determinants	R	N	LPI	C
Yu et al.	[41]	2008	Taiwan	Airports	Productivity growth with aircraft noise	NR	O	MLPI	S
Kjærsgaard et al.	[42]	2009	Denmark	Fishing trips	Environmental technical efficiency	R	O	No	–
Kumar and Khanna	[43]	2009	Annex I and other countries	Country-level data	Environmental efficiency and productivity	R	O	MLPI	C
Picazo-Tadeo and Prior	[44]	2009	Spain	Ceramic tile producers	Environmental efficiency and environmental regulatory impact	R	O	No	–
Zhang	[45]	2009	China	Province-level industry data	Environmental efficiency	R	O	No	–
Chang and Hu	[46]	2010	China	Chinese provinces	Energy productivity growth	NR	O	MPI	C
Kaneko et al.	[47]	2010	China	Thermal power sector	Shadow price of SO_2	R	O	No	–
Kumar and Managi	[48]	2010	Various countries	Country-level data	Environmental efficiency, environmental productivity, and Kuznets curve	R	O	MLPI	C
Kumar and Managi	[49]	2010	US	Electric utilities	Environmentally sensitive productivity growth and shadow price of SO_2	R	O	MLPI	C
Macpherson et al.	[50]	2010	US	Watersheds	Environmental and economic performance	R	N	No	–
Mandal and Madheswaran	[51]	2010	India	Cement industry	Environmental efficiency and regulatory cost	R	O	No	–

Mukherjee	[52]	2010	India	State-level manufacturing industry data	Energy efficiency	R	N	No	–
Murty et al.	[53]	2007	India	Thermal power plants	Technical and environmental efficiencies and shadow price	R	O	No	–
Nankano and Managi	[54]	2010	Japan	Prefecture-level data	Productivity growth with CO_2 emissions	R	N	LPI	C
Oh	[55]	2010	OECD countries	Country-level data	Environmentally sensitive productivity growth	R	O	MLPI	G
Oh	[56]	2010	Various countries	Country-level data	Environmentally sensitive productivity growth	R	O	MLPI	M
Oh and Heshmati	[57]	2010	OECD countries	Country-level data	Environmentally sensitive productivity growth	R	O	MLPI	S
Zhou et al.	[58]	2010	Various countries	Country-level data	Bootstrapped carbon emissions performance change	R	O	MLPI	C
Briec et al.	[59]	2011	Portugal	Hydroelectric plants	Productivity growth considering nature of technical change	R	O	LPI	C
Fujii et al.	[60]	2011	US and Japan	Manufacturing firms	Environmentally sensitive productivity growth	R	N	LPI	C
Ha et al.	[61]	2011	Japan	Air and rail companies	Comparing CO_2 emission efficiency between the air travel and rail travel industries	R	O	No	–
Khanna and Kumar	[62]	2011	US	S&P 500 firms' data	Environmental efficiency	R	O	No	–
Mahlberg and Sahoo	[63]	2011	OECD countries	Country-level data	Eco-productivity growth	NR	N	LPI	C
Mahlberg et al.	[64]	2011	EU	Country-level data	Eco-productivity growth	R	O	MLPI	C
Molinos–Senante et al.	[65]	2011	Spain	Wastewater treatment plants	Technical efficiency, shadow price of CO_2, and elasticity of substitution	R	O	No	–
Chiu et al.	[66]	2012	Annex I and other countries	Country-level data	Environmental inefficiency considering technology heterogeneities using metafrontier approach	R	O	No	–
Färe et al.	[67]	2012	US	Coal-fired power plants	Shadow prices and substitutability among pollutants	R	O	No	–
Halkos and Tzeremes	[68]	2012	Germany	Region-level data	Environmental efficiency	R	O	No	No
Heng et al	[69]	2012	US	Trucking industry	Environmentally sensitive productivity growth	R	N	MLPI	C
Krautzberger and Wetzel	[70]	2012	EU	Transportation industry	Environmentally sensitive productivity growth	R	O	MLPI	S
Matsushita and Yamane	[71]	2012	Japan	Power companies	Technical efficiency, shadow price of CO_2, and elasticity of substitution	R	O	No	–
Picazo-Tadeo et al.	[72]	2012	Spain	Olive growing farms	Eco-efficiency	R	O	No	–
Riccardi et al.	[73]	2012	Various countries	Cement production industry	Efficiency analysis incorporating CO_2	R	N	No	–
Wu et al.	[74]	2012	China	Regional industrial sector	Total-factor energy efficiency change	R	I	MLPI	C
Zhang et al.	[75]	2012	China	Province-level data	Environmentally sensitive productivity growth and environmental regulatory cost	R	O	MLPI	C
Zhao	[76]	2012	China	Province-level data	Environmentally sensitive productivity growth	R	O	MLPI	C
Zhou et al.	[77]	2012	Various countries	Fossil-fueled electricity generation industry	Energy and CO_2 performance	NR	O	No	–
Long et al.	[78]	2013	China	Chinese provinces	Environmental regulatory cost	R	O	No	–
Wang et al.	[79]	2013	China	Province-level data	Energy and CO_2 performance	NR	I	No	–
He et al.	[80]	2013	China	Iron and steel firms	Traditional energy efficiency, productivity, and environmentally sensitive productivity growth	R	O	MLPI	C
Yang and Wang	[81]	2013	China	Province-level data	Environmental efficiency and regulatory cost	R	N	No	–
Yuan et al.	[82]	2013	China	Prefecture-level data	Environmental efficiency and determinants	R	O	No	–
Zhang et al.	[83]	2013	Korea	Plant-level data	Energy efficiency and CO_2 performance	NR	N	No	–
Wang et al.	[84]	2013	China	Province-level data	CO_2 performance and determinants	R	O	No	–
Martini et al.	[85]	2013	Italy	Airports	Technical and environmental efficiency	R	O	No	–
Halkos and Tzeremes	[86]	2013	UK	Regional-level data	Environmental efficiency and determinants	R	O	No	–
Zhang and Choi	[94]	2013	China	Plant-level data	Total-factor carbon emission change	NR	N	MLPI	M
Zhang and Choi	[95]	2013	China and Korea	Plant-level data	Pure CO_2 emission change	NR	N	MLPI	M

Note. R: radial; NR: non-radial; O: output-oriented; I: input-oriented; N: non-oriented; DDF: directional distance function; MPI: Malmquist productivity index; MLPI: Malmquist–Luenberger productivity index; LPI: Luenberger productivity index; C: contemporaneous environmental technology; G: global environmental technology; M: metafrontier environmental technology; S: sequential environmental technology; SO_2: sulfur dioxide; NO_x: nitrogen oxides.

3.2.4. Bootstrapping MLPI

The calculation of the MLPI is based on linear programming, and therefore, MLPI is a deterministic approach that measures performance relative to an estimate of the true and unobservable production technology. Since estimates of technology are based on finite samples, the DDF and MLPI based on these estimates are subject to sampling variation of the frontier. Thus, one cannot know whether the productivity growth is statistically significant or not. The bootstrapping method proposed in [16] can be used to provide a statistical interpretation of the MLPI. For a DMU, if one dose not contains within the confidence intervals of MLPI, the improvement or deterioration in productivity growth of this specific DMU is statistically different from unity at the desired significance level. A case of using the bootstrapping approach for the MLPI can be found in [25,58].

Based on the basic DDF methodology and its various extensions, we could draw a figure of methodological structure of DDF model. Fig. 4 is the comparative diagram of the DDF-family. Firstly, we should decide the efficiency measure of the DDF that consist of measure type and orientation. Then, if the time dimension is considered, the various time-series measures should be employed. Bootstrapping technology could be used for both efficiency measure and time-series measures. The main findings of previous studies on the methodological aspect will be presented in the next section following the structure of Fig. 4.

4. Main findings of previous studies

This work collected 70 typical studies that used the DDF in E&E modeling. Major E&E-related journals as well as some well-read operations research/management science (OR/MS) and economics journals between 1997 and 2013 served as our primary sources. They are classified in Table 1 according to the following attributes: publication year, country/region, field of research/data and methodological aspect. The total number of publications show a significant increase over time since the DDF was first applied in E&E modeling in 1997 [17]. For instance, during the first half of the survey period (1997–2004), only 10 papers using the DDF in E&E studies could be found. Between 2005 and 2013 though, a total of 60 papers applied this topic. Table 1 shows that the studies originated from a wide spectrum of countries. Among those, China and the US were the most prolific, which may stem from the fact that both countries have had serious E&E problems, thus pushing their researchers to study the topic [89]. In the following sections, our main findings concerning previous studies in terms of field of research/data and methodological aspects are presented.

4.1. Field of research and data

This article uses the term “field of research and data” to refer to the industry and focus data-level (i.e., industrial level or firm level) of the study applying the DDF methodology. As shown in the fourth column of Table 1, the DDF methodology has been widely used in various industries across countries.

Thirteen studies (18.6% of the total examined by us) use the DDF to deal with specific issues in the manufacturing industry, accounting for the highest number of studies using this methodology. Eleven studies (15.7% of the total) have applied the DDF to the power generation industry. The transportation and agricultural industries have also employed the DDF, accounting for 6 (8.6%) and 4 (5.7%) studies of the total, respectively.

Regarding the data scales, 41.4% of the studies (i.e., 29 studies) applied the DDF at the micro (firm/plant) level; 18.6% (13), at the industrial level; and 40.0% (28), at the macro (country or regional) level. Therefore, the majority of the studies incorporated micro-level data into the DDF framework. This might be attributed to the fact that firm- or plant-level data can offer the advantage of homogeneity for efficiency benchmarking, according to the production theory. Nevertheless, it seems that there is an increasing tendency to apply the DDF at the macro level; this may reflect the global concern for sustainable development, namely, the interest in the benchmarking of environmental performance across countries as well as the ability of the DDF to measure environmental performance and the productivity index.

The fifth column of Table 1 refers to the “major issues addressed”, that is, the manner of application of the DDF. We observed that the DDF has been widely used in various applications pertaining to E&E studies. Among these, the most widely studied topics include environmental efficiency and environmentally sensitive productivity growth of different countries or industries. In fact, about a third of the total studies surveyed here deal with these areas. Again, this may be attributed to increasing concerns about sustainable development in recent years. Moreover, environmental regulatory costs [29,34] and shadow prices of pollutants (e.g. [22,27]) have also been studied frequently for different industries or countries.

It is observed that the parametric DDF is usually used for measuring shadow prices of pollutants [27,33,67,71], owing to its advantage of being an everywhere differentiable function and being easily manipulated algebraically. However, some studies have also used the non-parametric DDF to measure shadow prices [22,47]. The results of estimated shadow prices varied a lot. Different methodologies employed are one of the main reasons. In parametric estimations, results obtained from Shephard-translog specifications are consistently lower than results obtained using the DDF-quadratic specification. This is because the former estimation technique places the unit on a less steep portion of the production frontier than the latter [27].

Another widely employed application of the DDF is the use of its non-parametric form to measure environmental efficiency and productivity. However, certain studies have also utilized the parametric approach to measure environmental efficiency and productivity [49,84].

Energy efficiency measurement and monitoring constitutes an important topic in E&E studies. Certain studies have used the DDF to conduct energy efficiency analyses [52,77,83] and measure energy productivity growth [46]. Considering the ability of the DDF to distinguish between energy inputs and other inputs (capital and labor) while incorporating pollutant emissions, it is reasonable to believe that the DDF would play an increasingly important role in energy efficiency studies. In addition to the topics discussed above, the DDF has also been applied to study the efficiency and productivity of some specific energy-related industries, such as steam power companies [40,53,71]. Besides, as illustrated in [71,87], DDF is also an effective tool for studying the issue of emissions trading, another important topic in E&E studies.

4.2. Methodological aspects

As shown in Table 1, the methodological approach is further characterized by the efficiency measure and the time-series measure. The former includes measurement type and orientation option. The measurement type could be radial or non-radial efficiency measurement, and the orientation option can be output-oriented, input-oriented, or non-oriented. Time-series measure includes the kind of productivity index used by the study, that is, the MLPI or the LPI. Technology forms another aspect of the time-series measure, that is, the kind of environmental production technology the study employed, which includes the types of

environmental technologies (contemporaneous, global, metafrontier, or sequential) discussed previously in Section 3.2.

Firstly, we investigated the efficiency measure issue. It is found that almost all the studies we surveyed used the conventional radial efficiency measure of the DDF. That is, decreasing undesirable outputs (inputs) and increasing desirable outputs at the same rate to the frontier. Very few (only 6) studies employed the non-radial DDF, which provides more advantages than the radial version. It is found that the quantitative results of radial measure related to efficiency are higher than that of non-radial measure. It indicates that the radial measure may overestimate the efficiency because of neglecting the slack. It is also found that the non-parametric estimates of DDF were smaller than those obtained from the parametric function. The lower levels of inefficiency for the non-parametric estimates indicate that the piecewise linear DEA environmental technology is smaller than the technology corresponding to the parametric function.

Among these studies, two recent publications are worth highlighting, because they might suggest new directions for future research. One is [77], a study that developed a non-radial DDF with undesirable outputs to measure energy and carbon performance. The other is [83], a study that introduced the metafrontier approach into the non-radial DDF, so as to consider group heterogeneities.

For the orientation issue, it is found that the output-oriented DDF is the most widely used (37 studies), followed by the non-oriented DDF (16 studies). Looking at the research topic, we found that the output-oriented DDF is usually used for measuring environmental efficiency, while the non-oriented DDF is often employed to measure energy/carbon emission performance and total factor productivity.

Now, we discuss issues related to using the time-series methodology. About half the surveyed studies used the time-series methodology to measure environmentally sensitive productivity growth. Of these, the MLPI was the most frequently used (30 studies). Only six studies employed the LPI for measuring dynamic environmentally sensitive productivity change. This may be because the MLPI has had a longer application history than the LPI, and therefore, the latter may not be as well known as the MLPI.

Regarding the environmental production technology, among the studies that dealt with productivity growth using time-series data, contemporaneous environmental technology was still the most widely used approach among the various types of environmental technologies. Of the thirty studies that employed environmental technologies to measure productivity growth, only four used the sequential environmental technology. Applications employing global environmental technology and metafrontier environmental technology can be found in [55,56,94,95].

Among the studies that focused on environmental productivity growth, two publications, namely [25,58], are noteworthy, because they used the bootstrapping technology to incorporate statistical inference into the conventional MLPI, thus revealing a promising direction for future studies.

5. Suggestions for model selection and future research

Since a number of DDF models are available, researchers using the DDF to study E&E issues will inevitably face the problem of choosing an appropriate DDF model to apply. Therefore, it is hoped that the systematic summary of the various DDF approaches offered by this paper will provide guidance to authors in choosing the type of DDF.

First, one needs to pinpoint the most appropriate DDF approach: parametric or non-parametric. In general, the choice of the DDF approach depends on the research topic; as discussed previously, if one is interested is measuring environmental efficiency and productivity, the non-parametric specification might be a good choice, because it does not need the imposition of a functional form and is easy to calculate. On the other hand, if the topic focuses on shadow prices of pollutants, the parametric specification is likely to be more suitable, because it has the advantage of providing an estimated parametric representation of the technology that is everywhere differentiable and is easy to manipulate algebraically.

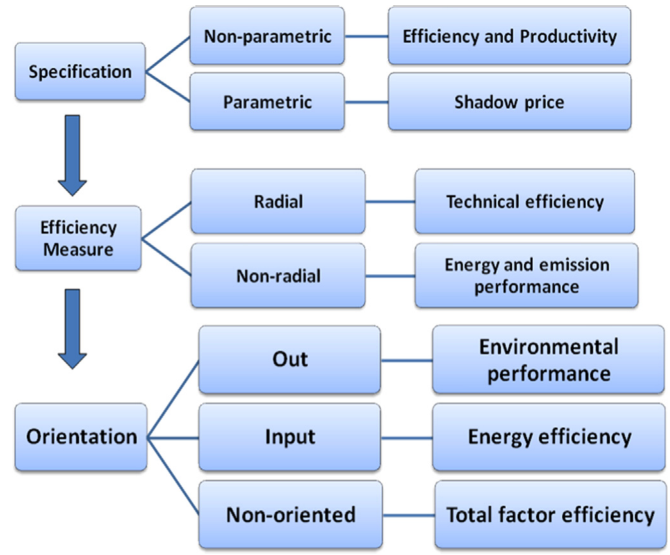


Fig. 5. Flow chart for DDF model selection.

For issues pertaining to efficiency measure, first, one needs to decide upon the use of the radial or non-radial DDF. The conventional radial DDF has been widely used for measuring environmental technical efficiency, because it is closely related to the shepherd distance function, and therefore, it can easily provide a Farrell-type efficiency measure. However, the radial DDF tends to overestimate the efficiency score in the presence of a slack variable, and it cannot provide specific factor efficiency, such as energy or carbon emission efficiency. Thus, if one wishes to focus on environmental technical efficiency, the radial DDF may be used. On the other hand, if energy efficiency or emission performance is the focus, the non-radial DDF might be more suitable. Regarding orientation selection, when considering pollutants, the output-oriented DDF measure might be more appropriate for measuring the pure environmental performance of DMUs. If the objective is to measure pure energy efficiency, an input-oriented model is suitable. If the focus of the study is a total-factor energy-environmental index, as suggested by [13], the non-oriented DDF measure might be more appropriate, because it can incorporate all inefficiencies of inputs and outputs. A flow chart for the model selection can be Fig. 5.

As to the time-series measure, either the MLPI or the LPI could be used to measure dynamic environmental productivity growth. It should be pointed out that previous studies have widely employed the MLPI based on the radial DDF, because the MLPI is a ratio measure of productivity growth that can be easily combined with the radial DDF, which is also a ratio efficiency measure. However, if one chooses the non-radial DDF measure to model environmentally sensitive productivity growth, the LPI might be the right choice, because the LPI is in the additive form, consistent with the non-radial DDF, which is also additive.

Various environmental production technologies provide us different choices to model environmentally sensitive productivity growth, depending on our data characteristics. If many infeasible solutions exist in the conventional MLPI, the Global MLPI may be a

suitable tool to overcome this problem. If the data contains group heterogeneities, leading to biased estimation for productivity growth, the metafrontier MLPI should be employed. If the sample size of the DMU is small or if the nature of the technology is to be considered, one can use the Sequential MLPI.

Once the DDF or the MLPI to be used are specified and the inputs and outputs are determined, the efficiency or productivity scores of DMUs can be calculated by some commercial software packages, such as MAXDEA, or by user self-coded programs built upon the R or MATLAB platforms. The "nonparaeff" package in R, developed by [88], is recommended, because it provides free tools for calculating the DDF and the MLPI.

Moreover, as the radial DDF neglects slack variables that tend to overestimate the efficiency score, we recommend that the non-radial DDF model be used for measuring energy and emissions performance. For measuring environmentally sensitive productivity growth, the non-radial DDF with the LPI (we refer to this as the "non-radial LPI") is recommended, because it can overcome the limitation of neglecting slack variables in the conventional MLPI.

Various extensions to the conventional MLPI, based on different environmental technologies, might also constitute directions for future study; a researcher could choose different extensions to the MLPI based on his/her research objective and data characteristics. Although the DDF is very useful in E&E studies, it is a deterministic approach; accordingly, one cannot determine whether the productivity growth is statistically significant. The bootstrapping MLPI or LPI can be used to add a statistical interpretation to the MLPI and its various extensions.

6. Conclusions

The DDF has become increasing popular in E&E studies in recent years. However, there is a lack of a comprehensive literature review in this field. It is hoped to fill this gap through our study, by presenting a survey of the various DDFs employed in E&E studies. We hope these findings will be useful to researchers in this field.

Our survey found that the DDF technology has been widely used in E&E studies for various industries, with applications in the manufacturing industry accounting for the largest number, followed by the power generation and the transportation sectors. Among the various E&E topics, environmental efficiency and environmentally sensitive productivity growth was the most widely studied.

While studying the methodological aspects, it is found that the radial efficiency measures and output-oriented model are the most widely used specifications. There has been a growing interest in the use of the MLPI in E&E studies. Among the studies that dealt with productivity growth using the MLPI, contemporaneous environmental technology was the most widely used.

This paper also discussed some issues pertaining to the selection of appropriate DDF models. Our findings suggest that the non-radial DDF and various extensions to the MLPI can provide promising insights in future studies.

Given the importance of E&E modeling techniques and the growing interest in sustainable development, it is believed that DDF models and their various extensions are likely to play an increasingly important role in E&E studies in the future.

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